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Owyang, Michael T.

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Michael T. Owyang†

Jeremy Piger‡

Howard J. Wall£

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Abstract

This paper estimates city-level employment cycles for 58 large U.S. cities and documents the substantial cross-city variation in the timing, lengths, and frequencies of their employment contractions. It also shows how the spread of city-level contractions associated with U.S. recessions has tended to follow recession-specific geographic patterns. In addition, cities within the same state or region have tended to have similar employment cycles. We find no evidence, that similarities in employment cycles are related to similarities in industry mix, although cities with more-similar high school attainment and mean establishment size have tended to have more-similar employment cycles.

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† Federal Reserve Bank of St. Louis. E-mail: owyang@stls.frb.org.
‡ University of Oregon. E-mail: jpiger@uoregon.edu.
£ Corresponding author, Lindenwood University. E-mail: hwall@lindenwood.edu

1. Introduction

National business cycles have long been characterized as a sequence of alternating periods of recession and expansion. In the United States, for example, the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) is tasked with determining official recession and expansion turning points. The determination of official business-cycle turning points is fairly opaque and untimely, and the turning points themselves are the only output from the effort. To address these shortcomings, a large literature has developed applying various statistical techniques to determine turning points and to examine underlying business cycle parameters.[1]

The advantages of these statistical approaches relative to the NBER's committee approach are their replicability, transparency, and timeliness. Also, because of these advantages, statistical approaches are readily applicable to a wide variety of questions. For example, using the Markov-switching model of Hamilton (1989), the notion of distinct cyclical phases has been extended to subnational economies, revealing significant differences in the timing, length, and occurrence of state-level recessions (Owyang, Piger, and Wall, 2005). This research has also revealed that periods of national recession usually contain a spatial component in that a recession spreads across the country in a geographic pattern. The effects of the 1990-91 NBER recession, for example, were first felt in the Northeast and the Far West before spreading to interior states. The recession receded in reverse, ending relatively quickly for interior states and lasting well after the end of the official recession for coastal states.

[1] See Harding and Pagan (2008) and Chauvet and Hamilton (2006) for surveys and discussions.

This paper extends this line of research by documenting the substantial variation in the cyclical movement of city-level employment, with the aim of finding the determinants of spatial variations over the cycle. The specific question we address is whether the geographic patterns of city-level employment cycles are simply reflections of differences in city industrial compositions or whether other, spatial mechanisms are responsible. As cities are arguably more relevant geographic delineations of local economies than are states, our analysis should provide a more accurate picture of subnational business-cycles. As we show, city-level data also allow us to examine in greater detail the extent to which spatially similar economies have similar business-cycle experiences. This greater accuracy and detail provided by our city-level cycles will assist us in explaining the variation in subnational employment cycles and their associated geographic patterns.

In section 2 we determine the timing of the employment cycle phases for 58 large cities, which we describe relative to each other and to the national business cycle in section 3. In section 4 we estimate the relative importance of industrial and geographic factors in determining cyclical similarities between cities, and in section 5 we extend the analysis to include potential roles for human capital, channels of monetary policy, industrial diversity, and agglomeration. Section 6 concludes.

2. Estimating City Employment Cycles

For our purposes, a city is either a Metro Division or a Metropolitan Statistical Area that is not divided into Metro Divisions. We use current MSA definitions, which restricts our analysis to post-1990, and examine payroll employment for 1990.Q1-2008.Q1 for all 58 cities that had average employment above 500,000 over the period. To determine the employment-cycle phases of our cities, we apply the Hamilton (1989) Markov-switching model independently to each. The simplest version of this model has employment cycle phases arising from the economy switching periodically between two different underlying regimes, each with its own mean growth rate.[2] Let μ_0 be the mean growth rate when the economy is in expansion, and let μ_1, which is normalized to be negative, be the difference between the mean growth rates in expansion and contraction. Specify the growth rate of employment, y_t, as

$$y_t = \mu_0 + \mu_1 S_t + \varepsilon_t, \tag{1}$$

The switching in (1) is governed by a state variable, $S_t = \{0,1\}$. Deviations from the mean growth rates are created by the stochastic disturbance, $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. When S_t switches from 0 to 1, the growth rate switches from μ_0 to $\mu_0 + \mu_1$. Because $\mu_1 < 0$, S_t switches from 0 to 1 at times when the economy switches from expansion to contraction, or vice versa.

The switching variable S_t is unobserved, meaning that we need to place restrictions on the probability process governing it. We assume that the process for S_t is a first-order two-state Markov chain, so any persistence in the regime is completely summarized by the value of S_t in the previous period. More specifically, the probability process driving S_t is captured by the transition probabilities $\Pr[S_t = j \mid S_{t-1} = i] = p_{ij}$. We estimate the model using the multi-move

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[2] This follows Owyang, Piger, and Wall (2005 and 2008); Owyang, Piger, Wall, and Wheeler (2008); and Hamilton and Owyang (2009). See Piger (2009) for a discussion of the basic Markov-switching models and their extensions.

Gibbs-sampling procedure for Bayesian estimation of Markov-switching models implemented by Kim and Nelson (1999).[3]

Simply put, the model estimates the growth rates of employment during contraction and expansion and determines for each period the probability that the economy is in contraction. To obtain this probability, the model compares the actual growth rate to the two regimes' growth rates while also accounting for the persistence of the series. If employment growth switches periodically between rates close to those of the two regimes, the probability of contraction will tend to be either close to zero or close to one. For present purposes we are interested only in the timing of cities' employment-cycle phases—as captured by their probabilities of contraction—and seeing the extent to which they are related to industrial composition and spatial consideration. As such, our analysis is silent on how well the cities do within each phase. Previous research has found that expansion growth rates were related to human capital and industrial structure, but that contraction growth rates were related only to the prevalence of manufacturing employment (Owyang, Piger, Wall, and Wheeler; 2008).

Before applying the model to our cities, we estimate the probability of employment contraction for the United States and compare it with the official NBER recession dates. Our results are illustrated by Figure 1 in which NBER recessions are indicated by the shaded areas. As is well-known, employment growth languished long after the 1990-91 and 2001 recessions had ended, which shows up here as the probability of employment contraction remaining high beyond the ends of NBER recessions. The figure also shows a less-well-known result: U.S.

[3] See Owyang, Piger, and Wall (2005) for a detailed description of the estimation procedure.

employment contractions began prior to official recessions for each of the last three recessions. Specifically, the 1990-91 recession was surrounded by an employment contraction that ran from 1990.Q2 to 1992.Q2, two quarters before the official recession began until five quarters after it ended. The 2000 recession was surrounded by an employment contraction that began in 2000.Q4, two quarters prior to the recession, and ended in 2003.Q3, seven quarters after the recession had ended. Finally, the U.S. was experiencing an employment contraction two quarters prior to the start of the official recession in 2008.Q1.

The model performs well for the cities in our sample, making the determination of contractionary periods fairly straightforward. Figure 2 shows the estimated contraction probabilities for the five largest cities in our sample. The first thing to note is the tendency for the contraction probabilities to be close to either one or zero, allowing for a clear separation of the employment series into contraction and expansion regimes. Also note the differences across cities: Although the cities' contractions tended to have occurred around the same general time periods, there were significant differences in their starting and ending dates, and, therefore, their lengths. For example, Los Angeles remained in contraction for much longer than the other four cities during the early 1990s, and Houston and Atlanta experienced the longest contractions of the early 2000s. Also notice that, by 2008.Q1, only three of the cities were in contraction, even though the national contraction had already begun. Three of these cities also exhibited some idiosyncratic switching: Los Angeles experienced a double-dip contraction during 2001-2003, Houston experienced a brief contraction in 1998-1999, and Washington's employment remained in its expansion phase throughout the early 2000s.

Figure 3 illustrates the estimated contraction probabilities for the five smallest cities in our sample. Although these cities tended to have experienced contractions around the same times as the national economy, idiosyncratic switches were common: Bethesda, Hartford, and Rochester experienced contractions in the mid-1990s; Buffalo and Rochester experienced contractions in the mid 2000s; and Bethesda and Providence were in contraction by 2006. Because smaller economies tend to have noisier data, the separation into the two regimes is not always as clean as for the largest cities. Even so, because the model accounts for persistence, the more-frequent regime switching for these cities is best explained by actual idiosyncratic events rather than by serially uncorrelated shocks.

Figures 2 and 3 also illustrate a number of relationships that we consider in subsequent sections. For example, even though Bethesda and Washington are in the same MSA, their employment cycles are very different from each another.[4] This is reminiscent of Voith (1998) and Chang and Coulson (2001), who consider whether city centers and their suburbs might have their own, but perhaps related, agglomeration processes. Notice also the similarity between the employment cycles of Buffalo and Rochester, two neighboring cities in the same state, and the different cycles of Providence and Hartford, two relatively close cities in different states.

Our results for all 58 cities are summarized in Table 1, which indicates for each quarter whether a city is in contraction or expansion.[5] For illustrative purposes the table is shaded for periods for which U.S. employment was in contraction. The main features of Figures 2 and 3

[4] See Wall (2010) for an analysis of the links between the employment cycles of neighboring cities.
[5] To achieve this binary identification, we adopt the convention that a contractionary quarter is one for which the probability of contraction is greater than 0.5.

discussed above also appear in Table 1: Although cities tended to have experienced contractions around the same times as each other, the starting and ending dates of these contractions differed a great deal; idiosyncratic contractions occurred for a number of cities during the mid 1990s and mid 2000s; and a significant number of cities were not in contraction yet by 2008.Q1. Finally, it was not uncommon for cities to completely miss the contractions felt elsewhere: five of the cities did not experience a contraction during the early 1990s, seven did not experience a contraction in the early 2000s, and Virginia Beach didn't experience a contraction during either period.

Figure 4 illustrates the differences across cities in the frequency of contraction over the period.[6] The figure shows that city-level contraction frequencies varied a great deal around that of the U.S., which was in an employment contraction 27 percent of the time. According to our results, 12 cities were in contraction between 42 and 69 percent of the time, whereas 15 cities were in contraction less than 21 percent of the time. All five cities in Ohio and Michigan were among the high-frequency group, along with three of the eight cities in California. The low-frequency cities were more evenly distributed, although proximity to high-contraction-frequency cities was no barrier to membership in this group. For example, Indianapolis and Louisville were in contraction relatively infrequently, despite their proximity to the high-frequency cities in Ohio and Michigan.

[6] The numbers underlying the figure are in the first column of Appendix 1.

3. Aggregated and Geographic Patterns of City Contractions

The city-level experiences outlined above can be reaggregated to illustrate their relationship with country-level recessions and employment contractions. In Figure 5, which simply tracks the number of cities in contraction over time, U.S. contractions occurred soon after the number of cities in contraction began to climb, and ended soon after the number began to fall.[7] At no time, however, were all 58 cities in contraction. For one, as pointed out above, during each U.S. contractionary period, several cities remained in expansion throughout. For another, some cities will have already exited their contraction before other cities had entered theirs. In fact, it is misleading to even call U.S. contractions "national" in that large geographic components of the nation do not experience them at the same time, if at all. The U.S. contraction and expansion switches reflect a rolling weighted aggregate of the local-level switches. It is more accurate, therefore, to say that aggregate U.S. contractions occur when enough local economies have entered into contraction to make nationally aggregated data switch into its contraction phase. The shock that results in local and, eventually, aggregate contractions might be experienced nationwide, but the whole nation need not enter into contraction for an aggregate contraction to occur. Nor, as we have seen, does there need to be an aggregate contraction for local economies to switch into contraction.

As illustrated by Owyang, Piger, and Wall (2005), state contractions tend to follow geographic patterns. They show, for example, that in the period surrounding the 1990-91 NBER

[7] One could make this figure more complicated by applying employment shares to obtain a weighted sum of city contractions, but because, as we show below, city size is unrelated to the occurrence of contractions this only changes the scale of the figure without affecting the story.

contraction, states on the east coast switched into contraction first, followed by states on the west coast, and the swathe of states between Texas and Montana missed out on the contraction entirely. As the state contractions ebbed during 1991, they receded back to the coastal states and lingered on for sometimes years longer. Although much of this pattern is evident in our city-level results, our data start in 1990 so we cannot see the pattern by which the early-switchers went into contraction. Even so, the official recession did not begin until 1990.Q4, yet many cities were in contraction at least two quarters earlier than this (Figure 6). A year later most, but not all cities were in contraction, and after another year had passed the contraction had receded to primarily coastal cities.

Figure 7 provides yearly snapshots of city contractions between 2000.Q3 and 2004.Q3 and illustrates a geographic pattern of contraction opposite that of Figure 6. In 2000.Q3—one quarter prior to the start of the U.S. employment contraction—10 cities far from the east and west coasts were in contraction. One year later, the contractions had spread to most of the rest of the cites in our sample, and by two years later had begun to recede from the cities on the Atlantic coast. By 2004.Q3, 12 cities were still in contraction, most of which were the same non-coastal cites which had been in contraction in 2000.Q3. The geographic pattern of contractions during this period shared the trait with the early 1990s period that the cities that switched into contraction early also tended to switch out of contraction late. However, the directions of the geographic patterns were completely opposite: The first was an "outside-in" contraction whereas the second was an "inside-out" one.

The geographic pattern for the beginning of the third contractionary period did not resemble that for the previous two. As shown by Figure 8, in 2007.Q1, one year prior to the start of the official recession and two quarters prior to the start of the U.S. employment contraction, 17 cities were already in contraction. These cities were concentrated in California and neighboring states, Florida, and the Rust Belt. As of 2008.Q1, the contraction had spread to many of the cities in the Southeast and to more of the Rust Belt. On the other hand, the Northeast, Northwest, and Mountain regions, along with Texas, were still relatively unscathed. Note that it is far too early to make a complete city-level accounting of this contractionary period because, for one thing, it is still far from over as of the time we are writing, and additional data might change the picture even of the quarters illustrated by Figure 8.

4. Industrial or Geographic Similarity?

Thus far, we have simply been documenting the differences in city-level contractions without attempting to explain them. We first need a measure of the extent to which cities differ from (or are similar to) one another, and we use their concordance, that is, the percentage of time that the two cycles are in the same regime (Harding and Pagan, 2002).[8] More specifically, the concordance between the employment cycles of cities *i* and *j* is

$$C_{ij} = \frac{100}{T}\sum_{t=1}^{T}\left[\left(S_{it} - S_{jt}\right) + \left(1 - S_{it}\right)(1 - S_{jt})\right], \qquad (2)$$

[8] See also Harding and Pagan (2006). Camacho and Perez-Quiros (2006) discuss this approach and propose an alternative framework.

where S_{it} and S_{jt} are the state variables for cities i and j and T is the number of time periods. The complete set of 1653 city-pair concordances is provided by Appendix 2 and they are summarized in Figure 9 by cities' employment cycles' concordances with the U.S. employment cycle.[9]

Why would two cities have widely differing employment cycles? Clearly there are periodic events at the national level that result in most cities experiencing contractions at some point within a period surrounding a national recession. But, around and during these periods, cities enter and exit their own contractions at different times. If city-level switches in and out of contractions were mostly reflections of the industrial composition of cities, then concordance should be high between two cities with similar industrial structures. Likewise, if two geographically similar cities tend to have similar employment cycles, then concordance should be higher for cities within the same region, state, or metro area.

This exercise is related to a longstanding question in the macro literature about whether fluctuations in aggregate economic variables are driven by microeconomic factors such as industry-level conditions, or aggregate factors that affected all industries (Lilien, 1982; Blanchard and Katz, 1986; Caballero, Engel, and Haltiwanger, 1997). The urban/regional analogue of the question splits the analysis along subnational lines, dividing fluctuations into industry, national, state, and regional factors (Clark, 1998; Carlino and Sill, 2001; Del Negro, 2002; Carlino and DeFina, 2004; Owyang, Rapach, and Wall, 2009). Kose, Otrok, and Whiteman (2003) took the question in the other direction, splitting national-level fluctuations into national, continental, and world factors.

[9] Each city's average concordance and its concordance with the U.S. employment cycle are provided in Appendix 1.

Although related to this previous work, which considers a variety of fluctuation types, our question is substantively different because of our characterization of economic fluctuations. The Markov-switching approach characterizes employment fluctuations by the occurrence of expansion and contraction phases and phase-specific growth rates. Our interest presently is in understanding the tendencies of city pairs to be in the same employment cycle phase, regardless of the cities' growth rates within the phases.

To separate the national, regional, state, city, and industry effects, we estimate the following, which regresses business-cycle similarity, as measured by concordance, on measures of industrial and geographic similarity:

$$\begin{aligned}\ln C_{ij} &= \alpha_0 + \alpha_i + \alpha_j \\ &\quad + \beta' IndustrySimilarity_{ij} \\ &\quad + \omega_1 PrincipalState_{ij} + \omega_2 SecondaryState_{ij} + \rho' Region_{ij} + \lambda Contiguous_{ij} + \mu_{ij}.\end{aligned} \tag{3}$$

Our primary measure of industrial similarity is a similarity index that measures the average closeness of employment shares across n major sectors.[10] Denoting the employment share of sector k in city i as x_{ik},

$$IndustrySI_{ij} = 1 - \frac{1}{n}\sum_{k=1}^{n}\left|x_{ik} - x_{jk}\right|. \tag{4}$$

$IndustrySI_{ij} \in (0,1]$ and equals 1 for two cities with identical employment shares for all n sectors. Geographic similarity is measured by four dummy variables: $PrincipalState_{ij}$ equals 1 if the principal cities of i and j are in the same state, $SecondaryState_{ij}$ equals 1 if the principal city of i is in the same state as outlying counties of j, $Region_{ij}$ equals 1 if the principal cities of i and j are

[10] We use annual data from the BLS for 1990-2008. The sectors are mining, logging, and construction; manufacturing; trade, transportation, and utilities; information; financial activities; professional and business services; education and health services; leisure and hospitality services; other services; and government.

in the same census region, and $Contiguous_{ij}$ equals 1 if i and j are contiguous.[11] Our estimation also includes city dummy variables to control for any factor that would affect a city's concordance the same across all other cities.

The results of our estimation of four versions of (3) are provided by Table 2. The first two estimations are extreme versions of the geography vs. industry question. From Model I, which assumes that geographic similarity is unrelated to concordance, we obtain a positive effect for similar industrial structures, but this result is not quite statistically significant ($p \approx 0.13$). From Model II, which assumes that the effect of industrial similarity is zero, we find that cities with principal cities in the same state or region tend have more-concordant employment cycles. On the other hand, we find no statistically significant relationship for contiguity or our secondary-state dummy.

Of course, geography and industry are likely to be related in that, for a variety of reasons, cities in the same parts of the country will tend to have similar industrial structures. By including only industrial or geographic similarity, as in Models I and II, we are not controlling for this simultaneity. From our results for Model III, which does control for simultaneity, it is clear that the positive role for industrial similarity found in Model I was due only to that variable capturing the relationship between geographic similarity and concordance. Specifically, inclusion of industrial similarity has no effect on our estimates of the link between geography and concordance, but inclusion of the geographic similarity dummies completely eliminates the

[11] There is a potential variable, $TertiaryState_{ij}$, for when the outlying counties of i and j are in the same state. We only have one pair for which this would equal 1 (Louisville and Cincinnati), so we do not include the variable.

positive coefficient on industrial similarity from Model I.[12] We conclude, therefore, that geographically similar cities tend to have similar employment cycles, but that there is no overall tendency for cities with similar industries to have similar employment cycles.

Model IV is a more-general specification that removes the restriction that the importance of regional similarity is the same across regions. Specifically, Model IV includes four regional-similarity dummies, one for each Census region. It shows that cities in the Northeast or Midwest regions tend to have more-similar employment cycles, but that there is no such relationship for cities in the Southeast or West. In addition, Model IV yields a stronger estimate of the relationship for the Northeast and Midwest, more than doubling that of the Northeast and more than quadrupling that of the Midwest. Note also that Model IV is preferred statistically to Models I – III in that the restrictions needed to obtain those models from IV are easily rejected by likelihood-ratio tests.

We return below to discussing the implications of Model IV, but before doing so we need to check whether our results are sensitive to the way that we have measured industrial similarity. We can think of two reasons why our industry similarity index might mask important differences in industrial structure and suppress the importance of industry in explaining concordance. First, the level of aggregation, which is limited by data availability, might be too blunt to capture differences that matter. In particular, our index does not distinguish between the durable and nondurable goods sectors, which might be problematic because the durable goods sector should be more sensitive to monetary policy, for example. Second, perhaps our index, which averages

[12] Note that the log likelihoods for Models II and III are identical, whereas a likelihood ratio test easily reject the null that there is no difference between Models III and I.

across all sectors, is masking the importance of a subset of sectors. Table 3 summarizes the results we obtain under measures of industrial similarity that ameliorate both of these concerns. Separate data for durable and nondurable sectors are unavailable for three of our cities, so the results in Table 3 are for 55 cities only.

Model IVa simply confirms that we obtain the same general results with our 55 cities as for Model IV with the full sample. Model IVb constructs the industrial similarity index with separate data for durables and nondurables, obtaining almost identical results to Model IVa. Model IVc dispenses with the similarity index and use measures of similarity for sectors whose sensitivity to the employment cycle should differ from the average:[13] manufacturing and mining, logging, and construction tend to be more sensitive than average, whereas the government sector tends to be less sensitive than average. Nonetheless, we do not find that similarity in any of these sectors is related to concordance. Finally, Model IVd differs from Model IVc in that it looks at durable-goods similarity rather than manufacturing similarity. Again, this has no effect on our results.

To summarize the importance of geographic factors in explaining the pattern of city contractions, the expected concordances from Model IV are provided in Table 4. For example, the employment cycles of two cities in different regions and states should be in synch 71.7 percent of the time, as obtained from the intercept term. If the two cities are in the same state in the South or West, where regional similarity does not matter, they should be in the same phase 80 percent of the time. But if they are in the same state in the Northeast of Midwest, where

[13] For each industry the similarity between cities *i* and *j* is $Similarity_{ij} = 1 - \left|\left(x_{ik} - x_{jk}\right)\right| / x_{ik}x_{jk}$.

regional similarities matter, they should be in the same phase 84.6 percent and 88 percent of the time, respectively. So, depending on where the cities are located, geographic similarity can have up to a 16.3 percentage point difference on their expected concordance.

Our city dummies can be as important in determining concordance as the geographic factors, as summarized by Table 5, which provides the estimated city effects from Model IV and converts them into percentage points. To prevent perfect collinearity, the city dummies were restricted to sum to 1, so each shows the difference relative to the average. A positive city effect indicates that, controlling for industrial and geographic similarity, the city tended to be more in synch with others than was the average city. The city effects for Charlotte and Miami meant that their concordances with others were more than 9 percentage point higher, whereas the city effects for Cincinnati, San Diego, and Detroit reduced their concordances with others by more than 12 percentage points. The geographic pattern of the city effects is shown by Figure 10. Because the regional effects have been taken out by the four regional dummies, cities with the highest and lowest city effects are scattered across the country. There seems to be some commonality within some states, however, particularly California, Ohio, New Jersey, and Florida.

These city effects can capture many things, including some that are not necessarily city specific. For example, they might be capturing state-specific effects if the relationship between concordance and being in the same state differs across states. Our state dummy does not distinguish between states, so any state-specific effect that differs from average will be captured by the city effects. The city dummies can also capture how a city's concordance with all other cities differs because of the city's very particular industrial structure. For example, a reasonable explanation for the large negative city effects for Detroit, Warren, San Diego, and Virginia Beach is that they have very specific industries that set them apart: automobile manufacturing in the cases of Detroit and Warren, and large military bases in the cases of San Diego and Virginia Beach. So, although these industries are important in explaining the employment cycles of their particular cities, they are not prevalent enough across cities to explain the geographic patterns depicted above.

5. Geography vs. Other Similarities

Our results above indicate that cities within the same state and perhaps the same region tend to have similar employment cycles. These results are driven either by the existence of spatial propagation whereby switches in and out of contractions spread via some underlying spatial links between cities, or cities in the same state or region tend to share certain characteristics that we have not controlled for. In this section we examine whether any of four sets of variables capturing similarities in human capital, monetary-policy channels, industrial diversity, and agglomeration are related to concordance.[14] Further, if they are related, we can compare their inclusion in the estimation on our estimates of geographic factors to see if they are driving our findings. The results of this exercise are provided in Table 6.

[14] The data for these variables are from the Census Bureau's *State and Metropolitan Area Data Book: 2006*, which included online updates as of February 9, 2009. This source typically provides data for one year because of changes in the composition of cities over time.

For the first set of results—Model V—we added three measures of human capital similarity to Model IV: a racial similarity index constructed along the lines of the industrial similarity index, and two measures of educational similarity (high school and bachelor's degree attainment) constructed along the lines of the single-industry similarity measures used above.[15] We know from previous research that cities' performance in either phase of the employment cycle is related to human capital as measured by education and race (Owyang, Piger, Wall, and Wheeler, 2008), and that the employment effects of recessions differ by race and education level (Hoynes, 2000; Engemann and Wall, 2010). Our question here is a bit different from this: Do similarities between cities in their racial composition and educational attainment make them more likely to be in the same phase of the employment cycle? Figures 11 and 12, which plot employment by race and educational attainment over our sample period, illustrate why one might think this to be so.

Note the period surrounding the aggregate employment contraction of the early 2000s (Figure 11): Black employment started falling in 1999, prior to the start of the aggregate contraction, whereas white employment peaked in 2001, after the aggregate contraction had begun. This suggests that cities with relatively similar racial compositions might have had relatively similar employment cycles, although the less-clear pattern around other turning points suggests otherwise. The differences between levels of educational attainment in the employment effects of contractions are more stark than those between races (Figure 12): The drop in

[15] We use four racial categories: white, black, Asian or Pacific Islander, and Native American. High school attainment is the share of the population over 25 years of age who have a high school diploma and have no additional education. Bachelor's degree attainment is the share of the same group with at least a bachelor's degree. All variables are for 2006.

employment for those with at least a bachelors degree is almost imperceptible whereas steep and early drops and late recoveries are the norm for those with only a high school diploma.[16] All else constant, cities with a labor force that has relatively many with only a high school diploma should, therefore, have a significantly different employment cycle from those with relatively many with at least a bachelors degree. As summarized by Table 6, when we add our human capital variables to Model IV, only the similarity in high school attainment is positive and statistically significant: Two cities with similar levels of high school attainment tend to have more-concordant employment cycles. Further, as Model IV is nested in this model, we can use a likelihood ratio test to reject the null that inclusion of these three variables has no effect on the model.

Previous research has found that the effects of monetary policy differ across states and regions (Carlino and Sill, 1998 and 1999), so it is possible that the city-level differences in employment cycles are driven in part by varying responses to monetary policy shocks. To capture differences in the magnitudes of various channels of monetary policy, Model VI adds three variables to Model V. The money channel, whereby monetary policy has larger effects on manufacturing than other industries, is already captured by our industry-similarity variable. To capture the broad credit channel, through which large firms are better able to absorb monetary policy shocks because of lower information and transactions costs, we have included the similarity in mean establishment size. Through the narrow credit channel small banks are thought to be more limited than large banks in finding alternative funding under tight monetary

[16] Note that these are the only education and racial categories available at a quarterly frequency and that the data on educational attainment begin in 1992.

policy, so we have included two bank-size measures. The first, average bank size—deposits per bank—represents this channel directly, and the second, banks per establishments, represents the availability of banking options for firms within a city. As shown in Table 6, we find evidence that the broad money channel is related to city business-cycle similarity in that the sign on the similarity of mean establishment size is positive and statistically significant.

The final two models, VII and VIII, examine whether employment cycle similarities can be attributed to similarities in industrial diversity and agglomeration, respectively. Simon (1988) found that a more industrially diversified city will have less frictional employment because its labor force will be more able to adjust to any negative shock. In our context, this might mean that two cities that are similarly diversified should have similar employment cycles because they could adjust more quickly during a contraction. It turns out, however, that although the similarity of industrial diversity is positively related to concordance, its effect is not statistically significant and inclusion of it has no statistically significant effect on the model. Finally, to test whether similarly agglomerated cities tend to have similar employment cycles, we estimated Model VIII, which adds similarity of city density and city size to Model VI. Neither variable is close to being statistically significant.

According to likelihood ratio tests, Model VI is preferred statistically to all other specifications we have considered. The same geographic variables that were significant in Model IV are still significant in Model VI, with only minor changes in their magnitudes. From Model VI we conclude that employment-cycle similarity is related to similarity in geography, high school attainment, and mean establishment size.

To see the extent to which these similarities matter, Table 7 calculates the expected concordances under the various combinations of these similarities. The first column of results, which is analogous to Table 4, assumes that two cities have the sample-average similarities in high school attainment and mean establishment size, but can differ geographically. Note first that for two such cities in different regions and states, the expected concordance is 73.1. If the two cities were in the same state in the South or West, they should have a concordance of 81.2. If they are in different Northeastern or Midwestern states their expected concordances are 77.3 and 79.5, respectively. If they are in the same state in the Northeast or Midwest, their expected concordances rise to 85.9 and 88.4, respectively.

The second and third columns of results assume, respectively, that the two cities have the same levels of high school attainment and mean establishment size. Having the same level of high school attainment adds 1.4 to 1.6 points to the concordances in the first column of results, whereas having the same mean establishment size adds 1.6 to 1.7 points. The final column assumes that the cities have the same high school attainment and mean establishment size, resulting in concordances of between 76.2 and 91.1, depending on the level of geographic similarity. Our addition of human capital and monetary-policy channels contributes something, but not a whole lot, to our explanation of city concordances. Geographic similarity is still explaining large chunks of the differences in concordance. Perhaps there are other city-level characteristics that we have not considered that are being picked up as geographic similarity. Alternatively, the geographic similarity is picking up a spatial propagation mechanism such as trade by which turns in the employment cycle are spread from city to city.

6. Summary and Conclusions

We estimated city-level employment cycles for 58 large U.S. cities and documented the substantial cross-city variation in the timing, lengths, and frequencies of their employment contractions. We also showed how the spread of city-level contractions associated with U.S. recessions has tended to follow recession-specific geographic patterns. Cities within the same state or region have tended to have similar employment cycles, but cities with similar industrial mixes did not. Additionally, cities with more-similar high school attainment and mean establishment size have tended to have more-similar employment cycles.

According to our statistically preferred model, two cities that are geographically dissimilar and have the sample-average similarities in high school attainment and mean establishment size should be in the same employment cycle phase 73.1 percent of the time. However similar the cities' high school attainment and mean establishment size, geographic similarity can raise their concordance by as much as 15.3 percentage points (if the cities are in the same state in the Midwest). For any degree of geographic similarity, having identical high school attainment and mean establishment size will raise concordance by 3.1 points.

Appendix 1. Summary Statistics

	Contraction Frequency	Mean Concordance	Concordance with U.S.
Atlanta-Sandy Springs-Marietta, GA	0.361	79.1	91.7
Austin-Round Rock, TX	0.167	76.8	80.6
Baltimore-Towson, MD	0.292	79.4	90.3
Bethesda-Gaithersburg-Frederick, MD	0.514	70.7	81.9
Boston-Quincy, MA	0.278	81.1	91.7
Buffalo-Niagara Falls, NY	0.389	72.5	80.6
Charlotte-Gastonia-Concord, NC-SC	0.278	81.2	88.9
Chicago-Naperville-Joliet, IL	0.264	81.0	87.5
Cincinnati-Middletown, OH-KY-IN	0.681	59.6	65.3
Cleveland-Elyria-Mentor, OH	0.569	67.3	73.6
Columbus, OH	0.444	70.3	72.2
Dallas-Plano-Irving, TX	0.208	80.3	87.5
Denver-Aurora, CO	0.153	77.0	81.9
Detroit-Livonia-Dearborn, MI	0.681	56.4	59.7
Edison, NJ	0.083	72.1	75.0
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	0.278	71.1	77.8
Fort Worth-Arlington, TX	0.264	80.7	90.3
Hartford-West Hartford-East Hartford, CT	0.472	65.4	75.0
Houston-Sugar Land-Baytown, TX	0.333	76.2	80.6
Indianapolis-Carmel, IN	0.194	78.0	86.1
Jacksonville, FL	0.333	79.0	94.4
Kansas City, MO-KS	0.347	74.8	84.7
Las Vegas-Paradise, NV	0.306	77.9	86.1
Los Angeles-Long Beach-Glendale, CA	0.347	75.1	84.7
Louisville-Jefferson County, KY-IN	0.194	74.6	80.6
Memphis, TN-MS-AR	0.528	71.1	80.6
Miami-Miami Beach-Kendall, FL	0.236	81.5	90.3
Milwaukee-Waukesha-West Allis, WI	0.236	80.1	90.3
Minneapolis-St. Paul-Bloomington, MN-WI	0.403	77.2	87.5
Nashville-Davidson--Murfreesboro, TN	0.194	75.0	83.3
Nassau-Suffolk, NY	0.139	72.1	77.8
Newark-Union, NJ-PA	0.181	69.7	73.6
New Orleans-Metairie-Kenner, LA	0.472	62.7	72.2
New York-White Plains-Wayne, NY-NJ	0.292	80.2	90.3
Oakland-Fremont-Hayward, CA	0.597	59.9	59.7
Oklahoma City, OK	0.139	76.9	80.6
Orlando-Kissimmee, FL	0.264	78.8	90.3
Philadelphia, PA	0.306	80.5	88.9
Phoenix-Mesa-Scottsdale, AZ	0.417	77.2	91.7
Pittsburgh, PA	0.292	76.9	79.2
Portland-Vancouver-Beaverton, OR-WA	0.194	79.8	86.1
Providence-New Bedford-Fall River, RI-MA	0.194	74.3	83.3
Richmond, VA	0.236	80.2	90.3
Riverside-San Bernardino-Ontario, CA	0.264	62.1	62.5
Rochester, NY	0.375	72.0	79.2
Sacramento-Arden-Arcade-Roseville, CA	0.236	63.6	65.3
St. Louis, MO-IL	0.264	81.0	87.5
Salt Lake City, UT	0.167	76.4	77.8
San Antonio, TX	0.319	76.0	81.9
San Diego-Carlsbad-San Marcos, CA	0.667	58.5	61.1
San Francisco-San Mateo-Redwood City, CA	0.458	70.7	76.4
San Jose-Sunnyvale-Santa Clara, CA	0.208	78.0	81.9
Santa Ana-Anaheim-Irvine, CA	0.347	70.8	79.2
Seattle-Bellevue-Everett, WA	0.181	76.9	81.9
Tampa-St. Petersburg-Clearwater, FL	0.347	78.8	93.1
Virginia Beach-Norfolk-Newport News, VA-NC	0.028	67.8	69.4
Warren-Troy-Farmington Hills, MI	0.486	64.9	68.1
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.125	72.5	79.2
Cross-City Average	0.285	73.8	81.9
United States	0.276		

Appendix 2: Cross-City Concordances (Ordered by City Size)

	Los Angeles	Chicago	Houston	Atlanta	Washington	Dallas	Philadelphia	Phoenix	Minneapolis	Boston	Santa Ana-Anaheim	Seattle	St. Louis	Baltimore	Warren	Tampa	San Diego	Nassau-Suffolk	Riverside	Denver	Pittsburgh	Cleveland	San Francisco	Orlando	San Jose	Miami	Oakland	Edison	Portland	Cincinnati	Newark	Kansas City	Columbus	Las Vegas	Detroit	Indianapolis	Sacramento	Fort Worth	Milwaukee	Charlotte	San Antonio	Fort Lauderdale	Virginia Beach	Austin	Nashville	Salt Lake City	Memphis	Richmond	Jacksonville	Louisville	New Orleans	Providence	Bethesda	Hartford	Oklahoma City	Buffalo	Rochester
New York	92	92	88	82	83	92	96	88	78	96	81	83	92	94	58	83	63	85	64	83	81	67	83	81	86	94	61	79	88	61	81	78	68	82	53	85	67	89	86	90	81	74	68	82	79	82	74	89	85	79	63	76	78	82	85	85	81
Los Angeles		83	79	76	78	83	88	82	72	88	86	78	83	86	53	78	68	79	72	75	72	61	86	75	78	86	67	74	79	58	75	72	63	76	50	79	69	81	78	82	72	71	65	74	74	74	68	81	79	71	57	74	72	82	76	76	75
Chicago			88	90	81	92	96	79	86	96	72	86	##	89	67	83	60	79	58	86	89	67	81	83	92	97	58	82	90	58	78	86	76	82	58	88	58	92	89	99	89	76	71	88	82	90	74	92	82	82	63	79	75	74	88	76	75
Houston				81	74	88	92	75	74	89	68	79	88	85	65	74	61	75	57	79	88	71	82	76	88	85	65	69	83	65	74	76	75	78	60	78	60	88	82	86	82	64	64	81	69	83	75	79	78	75	72	67	71	69	81	75	76
Atlanta					71	82	86	86	93	86	74	79	90	82	76	90	64	69	60	79	85	76	76	90	82	88	63	72	83	68	68	88	81	83	65	83	60	88	88	92	88	78	67	81	81	81	83	88	89	78	72	83	82	67	78	72	71
Washington						81	82	71	67	85	78	72	81	83	47	75	46	99	75	72	69	53	67	72	78	83	44	96	76	44	94	67	57	74	42	82	78	78	75	79	69	79	85	71	82	71	60	83	76	68	51	85	61	65	79	71	69
Dallas							90	79	78	93	72	92	92	89	61	83	54	79	64	92	86	64	75	86	94	94	61	79	93	53	75	78	74	88	53	88	67	94	92	90	81	74	76	90	79	90	68	89	85	88	68	76	69	74	90	79	81
Philadelphia								83	82	97	76	82	96	93	63	82	64	83	60	82	85	71	85	79	90	93	63	78	86	63	82	82	72	81	57	83	63	90	85	94	85	72	67	83	78	86	78	88	83	78	64	75	79	78	83	81	79
Phoenix									90	83	82	74	79	85	71	93 100	69	72	71	74	71	79	74	85	74	82	68	67	78	74	68	76	72	89	63	78	74	82	82	81	74	78	61	72	75	69	86	82	92	72	67	78	90	72	72	83	76
Minneapolis										82	72	75	86	78	81	92	68	65	64	75	78	81	69	86	78	83	67	68	79	72	64	83	82	88	69	79	67	83	83	88	81	79	63	76	76	76	88	83	88	74	65	79	89	63	74	74	72
Boston											76	85	96	93	63	85	61	83	60	85	85	68	82	82	90	96	60	81	89	60	79	82	72	83	57	86	63	93	88	94	85	75	69	86	81	86	75	90	86	81	64	78	76	78	86	81	79
Snta Ana-Anah												67	72	78	53	81	68	79	83	64	61	61	75	75	67	75	67	74	68	58	75	64	60	79	50	74	81	69	69	71	61	79	68	63	76	63	68	78	82	60	54	82	72	71	68	68	67
Seattle													86	83	67	78	49	71	61	97	86	58	72	86	86	89	56	76	96	47	67	81	68	79	47	85	58	89	92	88	83	68	79	96	82	93	63	86	79	93	65	76	64	68	90	74	78
St. Louis														89	67	83	60	79	58	86	89	67	81	83	92	97	58	82	90	58	78	86	76	82	58	88	58	92	89	99	89	76	71	88	82	90	74	92	82	82	63	79	75	74	88	76	75
Baltimore															58	86	57	85	61	83	81	67	81	83	83	92	56	79	88	58	83	78	65	82	53	85	64	89	86	90	81	74	68	82	82	79	74	92	88	79	63	79	78	79	85	82	83
Warren																72	68	46	47	67	72	86	56	72	61	64	69	51	68	78	47	72	85	71	75	63	50	67	69	68	75	63	54	68	65	68	76	64	71	68	68	63	69	43	63	65	64
Tampa																	63	74	67	78	75	75	69	92	78	86	61	74	82	67	69	81	74	93	64	85	69	86	86	85	78	85	68	76	82	74	82	89	96	76	68	85	83	68	79	76	75
San Diego																		47	60	46	60	79	76	54	54	57	93	42	50	76	49	51	78	64	71	50	57	54	51	58	57	56	36	47	44	50	72	54	61	42	50	50	68	56	47	61	63
Nassau-Suffolk																			76	71	68	54	68	71	76	82	46	94	75	46	96	65	56	72	40	81	79	76	74	78	68	78	83	69	81	69	61	82	75	67	50	83	63	67	78	72	71
Riverside																				58	53	53	61	67	61	61	67	74	60	47	72	50	57	74	42	65	92	58	61	57	47	74	76	57	63	57	57	64	68	54	46	74	61	54	63	60	61
Denver																					86	58	69	86	89	89	53	76	96	47	67	81	68	79	47	85	61	89	92	88	83	68	82	99	82	96	63	86	79	96	68	76	64	68	93	74	75
Pittsburgh																						72	78	83	86	86	64	74	90	61	69	81	82	76	61	82	53	89	89	90	92	65	68	88	76	88	74	83	76	82	71	74	67	65	82	74	72
Cleveland																							64	69	64	64	81	49	63	89	56	69	88	74	81	60	58	69	67	68	72	63	46	60	60	60	90	64	76	63	71	60	78	51	57	74	72
San Francisco																								67	75	78	75	63	74	61	67	69	63	65	56	68	56	78	72	82	78	57	51	71	65	71	71	75	71	65	57	63	69	76	68	71	72
Orlando																									81	86	58	76	90	58	67	83	76	90	56	90	67	89	94	85	81	79	76	85	85	82	74	89	93	85	71	88	75	65	85	74	78
San Jose																										89	61	76	88	53	75	78	74	82	53	85	67	92	86	90	81	71	76	90	74	93	68	83	79	85	68	71	69	68	90	74	75
Miami																											56	85	93	56	78	83	74	85	56	90	61	92	92	96	86	79	74	88	85	88	71	94	85	85	63	82	72	76	90	79	78
Oakland																												40	54	75	47	50	82	68	69	51	64	58	56	57	56	54	43	54	43	57	71	53	63	49	57	49	67	51	51	63	67
Edison																													81	40	90	71	58	72	40	86	74	76	79	81	74	81	89	75	86	75	56	85	72	72	47	89	57	61	81	67	65
Portland																														51	71	85	72	83	51	89	60	93	96	92	88	72	78	94	86	92	67	90	83	92	64	81	68	72	92	78	79
Cincinnati																															47	67	76	63	86	51	53	58	56	60	64	54	35	49	51	49	85	56	65	51	74	51	72	49	46	65	61
Newark																																64	57	68	42	76	75	72	69	76	67	74	79	65	76	68	60	78	71	63	51	79	64	63	74	71	67
Kansas City																																	68	74	64	82	50	83	86	88	89	68	68	82	85	82	79	83	79	85	71	76	72	63	76	68	67
Columbus																																		81	76	69	60	74	74	75	74	69	58	69	61	72	78	71	72	64	67	67	71	50	69	69	71
Las Vegas																																			63	83	76	85	85	81	71	83	72	78	75	78	78	85	92	75	67	81	79	64	83	75	76
Detroit																																				49	44	56	53	60	61	57	35	49	49	49	76	56	60	49	71	51	61	46	46	57	58
Indianapolis																																					65	88	90	86	82	78	81	83	89	83	67	90	83	83	61	83	68	67	89	72	76
Sacramento																																						61	61	57	47	74	79	60	63	60	63	64	71	57	51	74	67	54	65	63	61
Fort Worth																																							94	93	86	71	71	90	82	88	74	89	88	88	68	76	75	74	88	82	83
Milwaukee																																								90	86	74	76	90	85	88	71	92	88	90	68	82	72	71	88	79	81
Charlotte																																									90	75	69	89	83	89	75	93	83	83	64	81	76	75	86	78	76
San Antonio																																										65	65	85	85	85	79	83	76	85	68	74	69	65	79	71	69
Fort Lauderdale																																											75	67	78	67	67	79	81	64	53	86	68	58	75	69	63
Virginia Beach																																												81	81	81	50	76	69	78	56	83	51	50	83	58	60
Austin																																													81	97	64	85	78	94	67	75	65	67	92	72	74
Nashville																																														78	67	88	81	83	58	89	65	64	81	72	71
Salt Lake City																																															64	82	75	92	67	72	65	64	92	69	71
Memphis																																																71	81	67	75	67	85	58	61	69	68
Richmond																																																	88	82	63	88	72	74	88	76	78
Jacksonville																																																		78	72	83	82	69	81	78	79
Louisville																																																			72	72	63	64	89	72	74
New Orleans																																																				58	60	47	64	58	57
Providence																																																					68	61	75	67	65
Bethesda																																																						68	63	76	69
Hartford																																																							67	75	68
Oklahoma City																																																								72	76
Buffalo																																																									82

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Figure 1. Employment-Contraction Probability for the United States
Shaded Areas are NBER Recessions

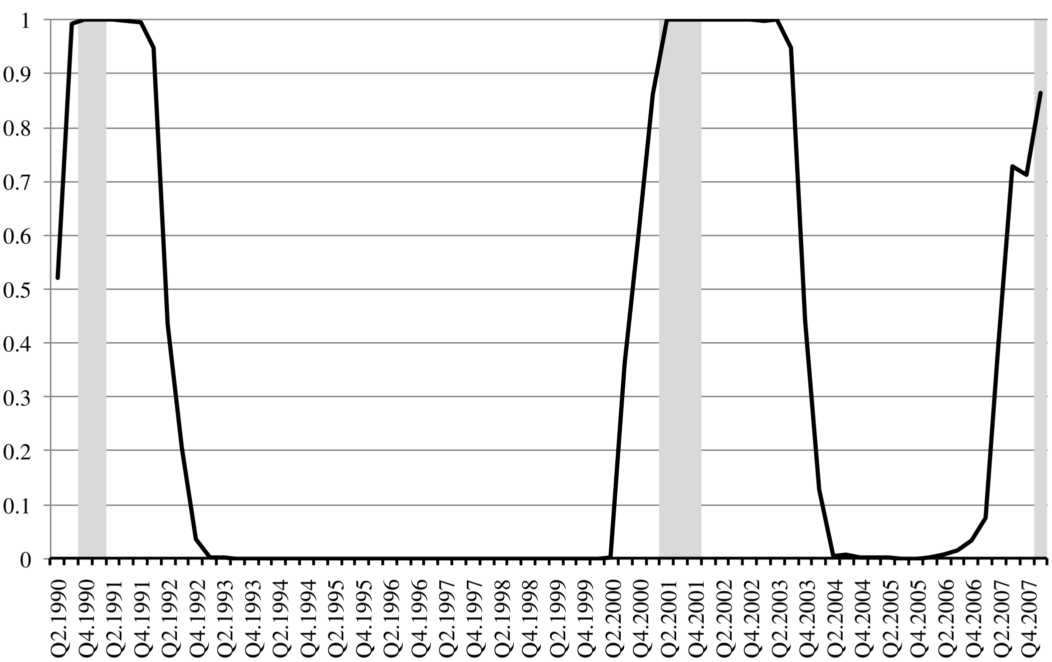


Figure 2. Contraction Probabilities for the Six Largest Cities
Shaded Areas Are U.S. Employment Contractions

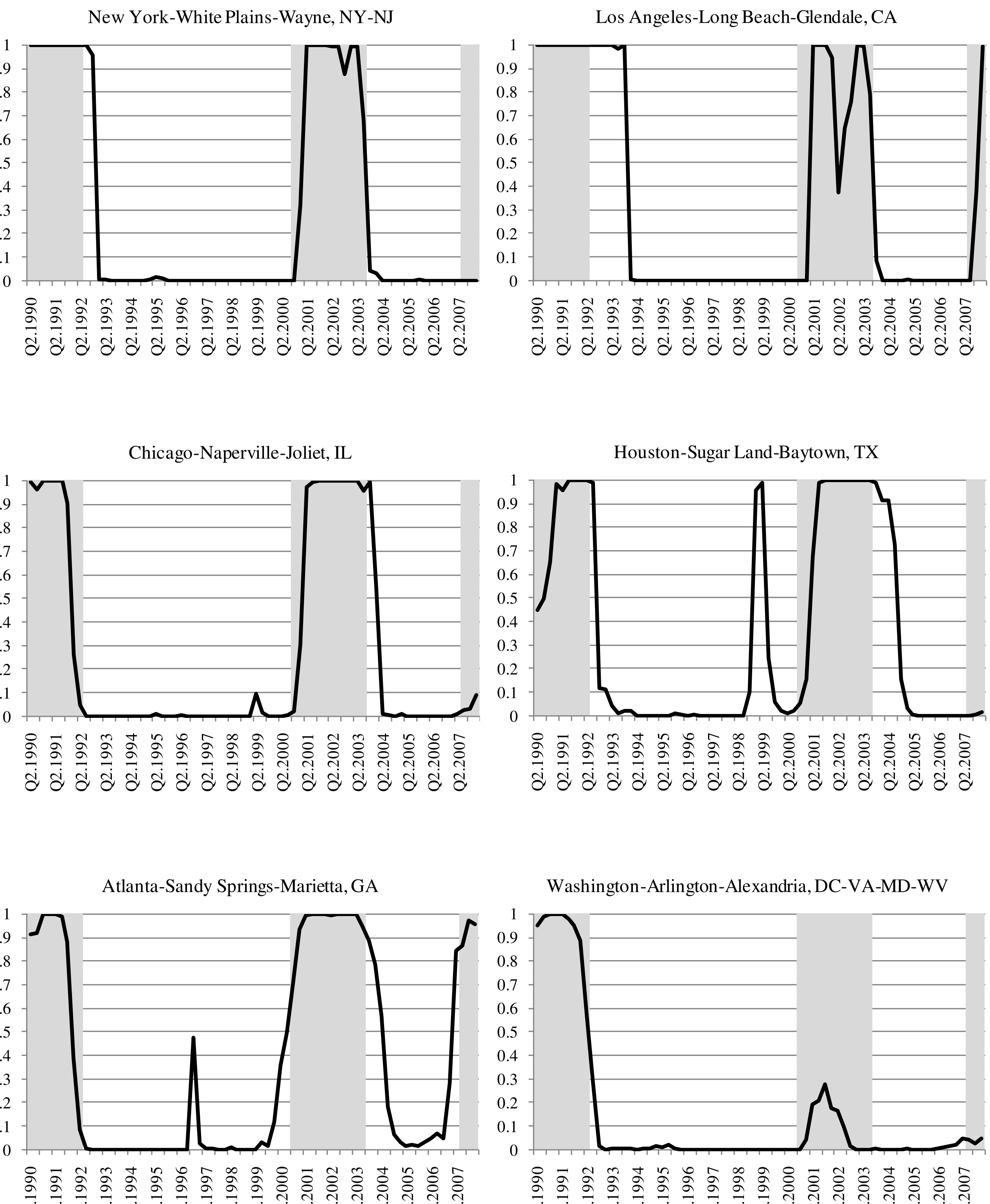


Figure 3. Contraction Probabilities for the Six Smallest Cities

Shaded Areas Are U.S. Employment Contractions

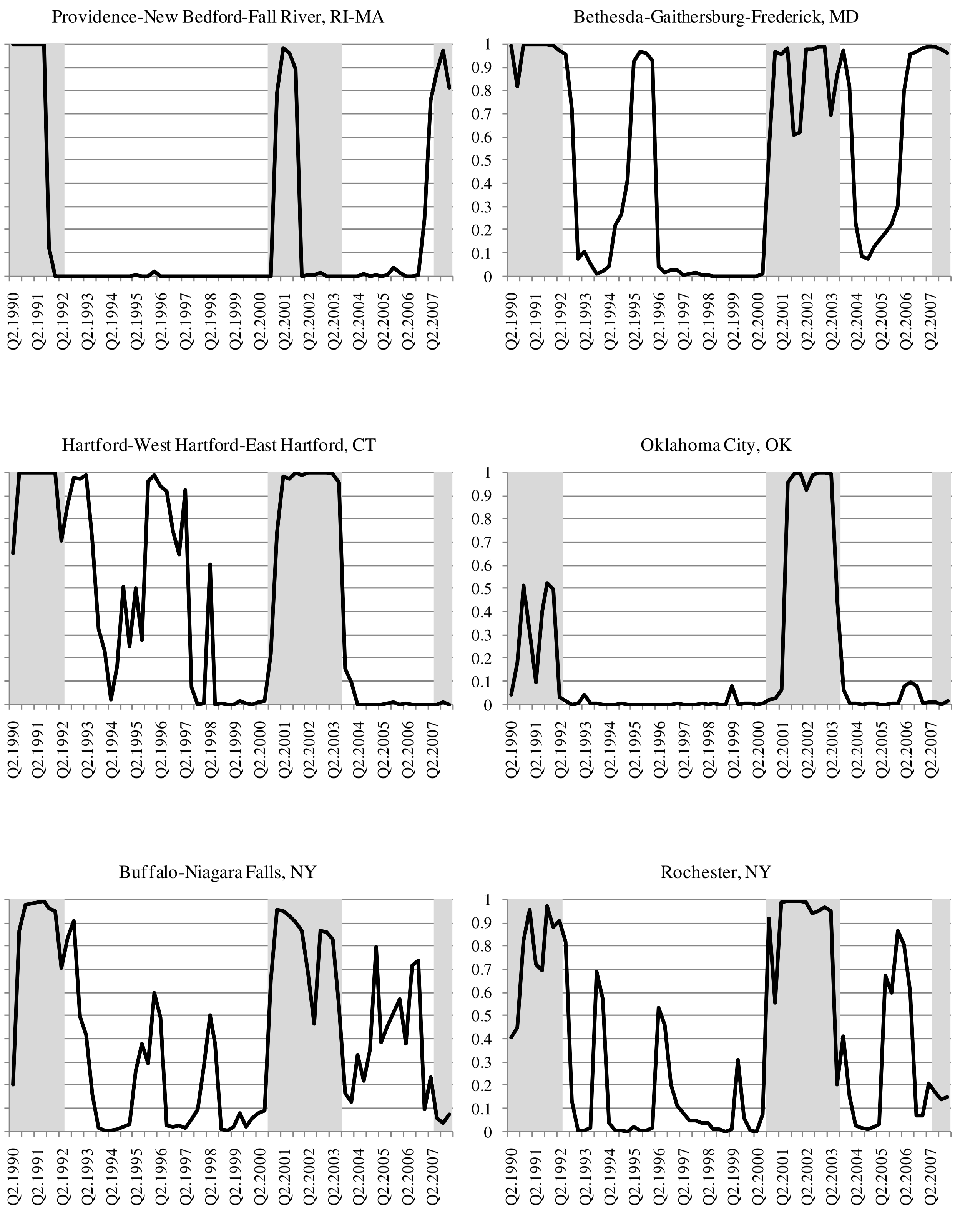


Figure 4.

Frequency of Recession Across Cities, 1990-2008
(Percentage of Time in Contraction)

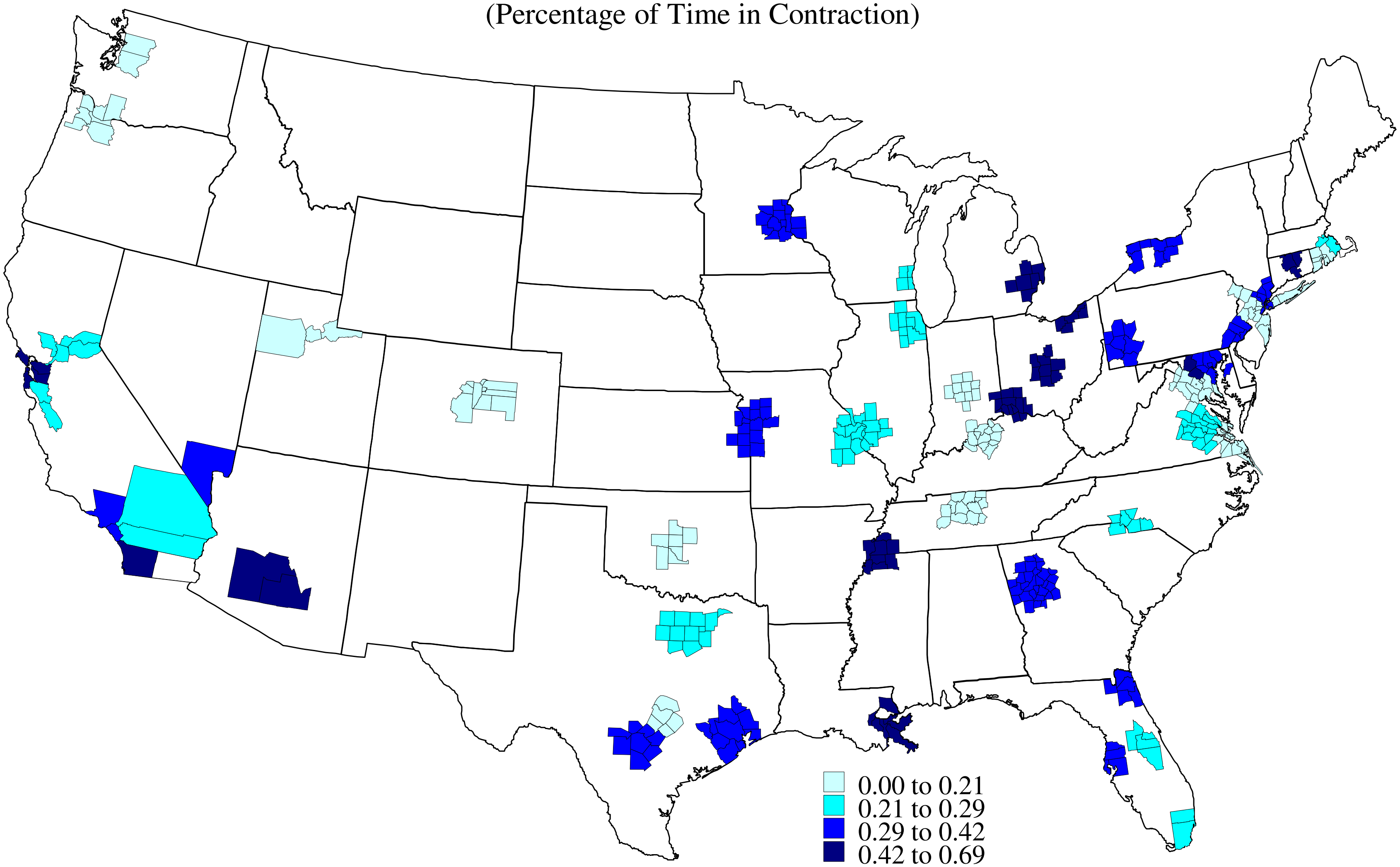
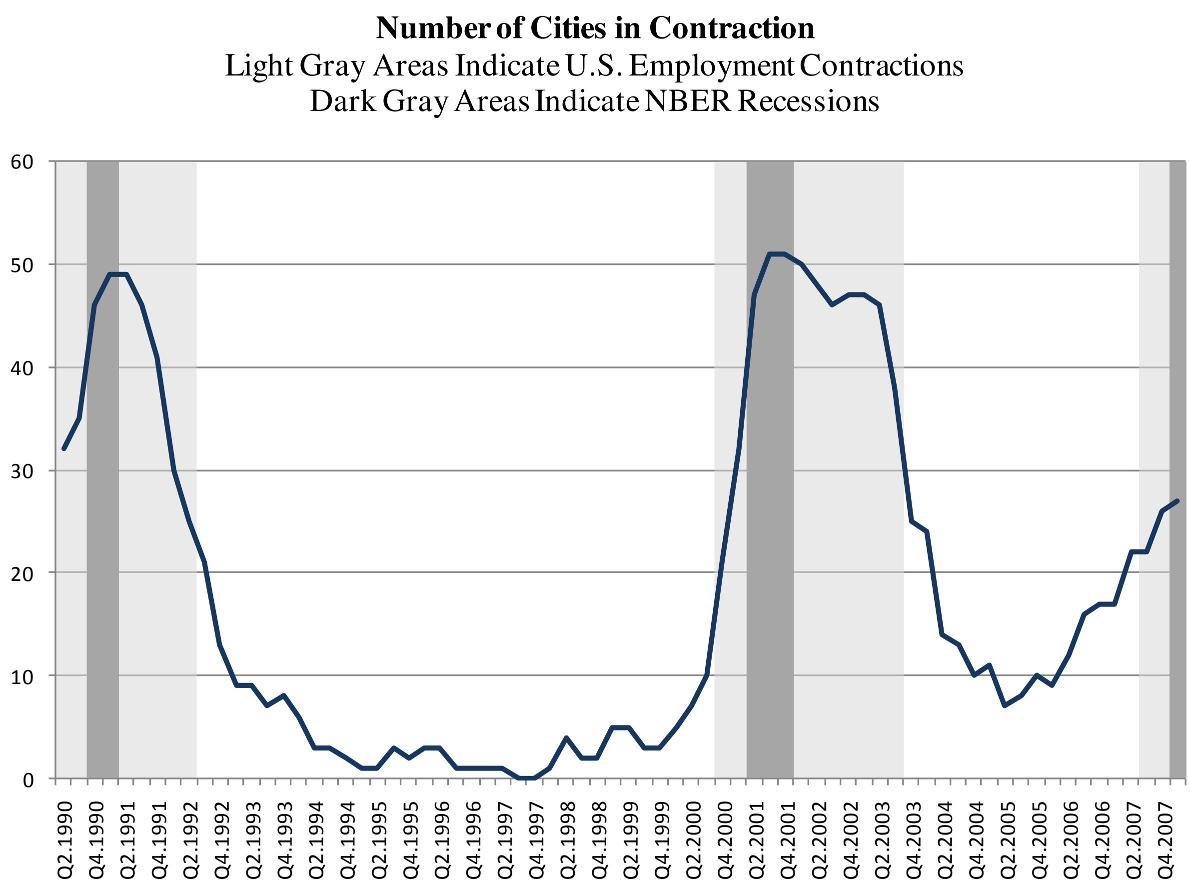


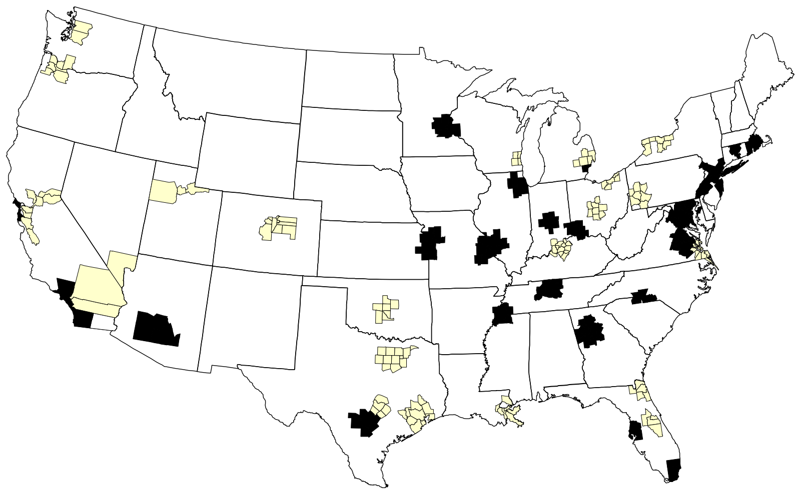
Figure 5.



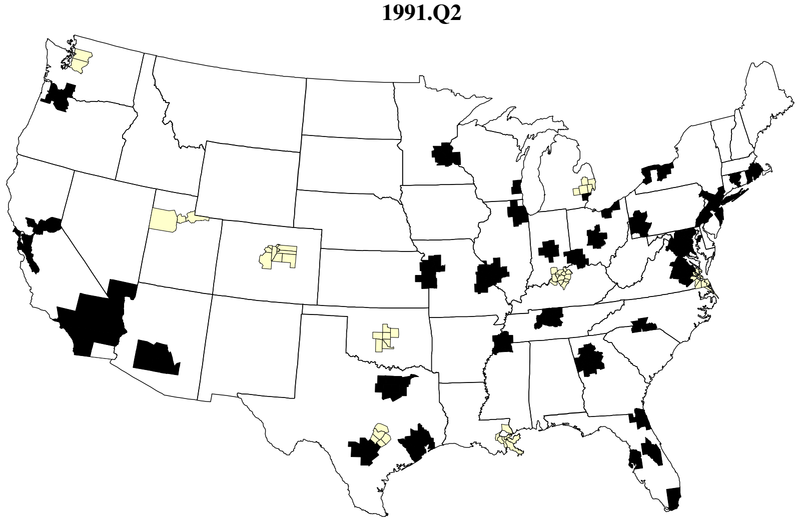
Number of Cities in Contraction
Light Gray Areas Indicate U.S. Employment Contractions
Dark Gray Areas Indicate NBER Recessions
60
50
40
30
20
10
0
Q2.1990
Q4.1990
Q2.1991
Q4.1991
Q2.1992
Q4.1992
Q2.1993
Q4.1993
Q2.1994
Q4.1994
Q2.1995
Q4.1995
Q2.1996
Q4.1996
Q2.1997
Q4.1997
Q2.1998
Q4.1998
Q2.1999
Q4.1999
Q2.2000
Q4.2000
Q2.2001
Q4.2001
Q2.2002
Q4.2002
Q2.2003
Q4.2003
Q2.2004
Q4.2004
Q2.2005
Q4.2005
Q2.2006
Q4.2006
Q2.2007
Q4.2007

Figure 6. Early 1990s Contractions
Cities in Contraction are in Black

1990.Q2



1991.Q2



1992.Q2

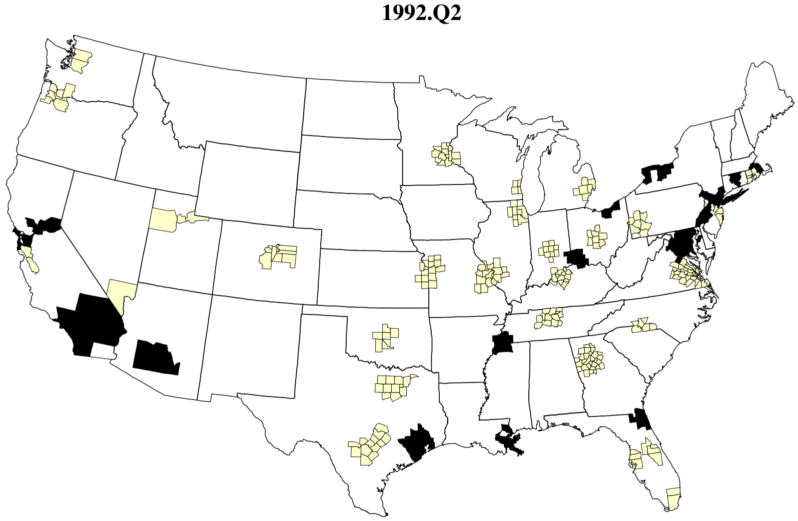
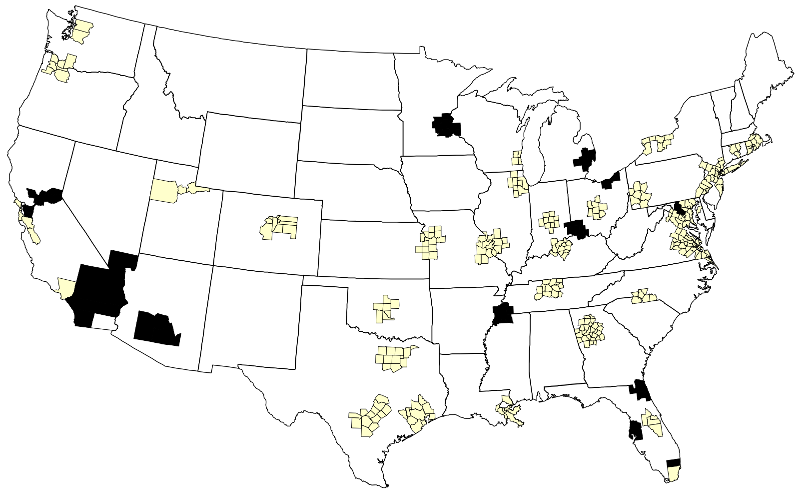


Figure 7. Early 2000s Contractions
Cities in Contraction are in Black

Figure 8. Late 2000s Contractions
Cities in Contraction are in Black

2007.Q1



2008.Q1

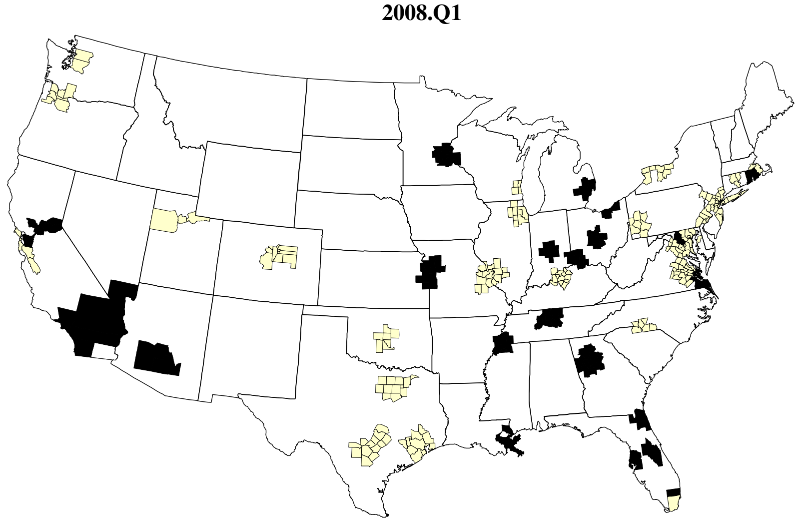


Figure 9.

Concordances Between City and U.S. Business Cycles

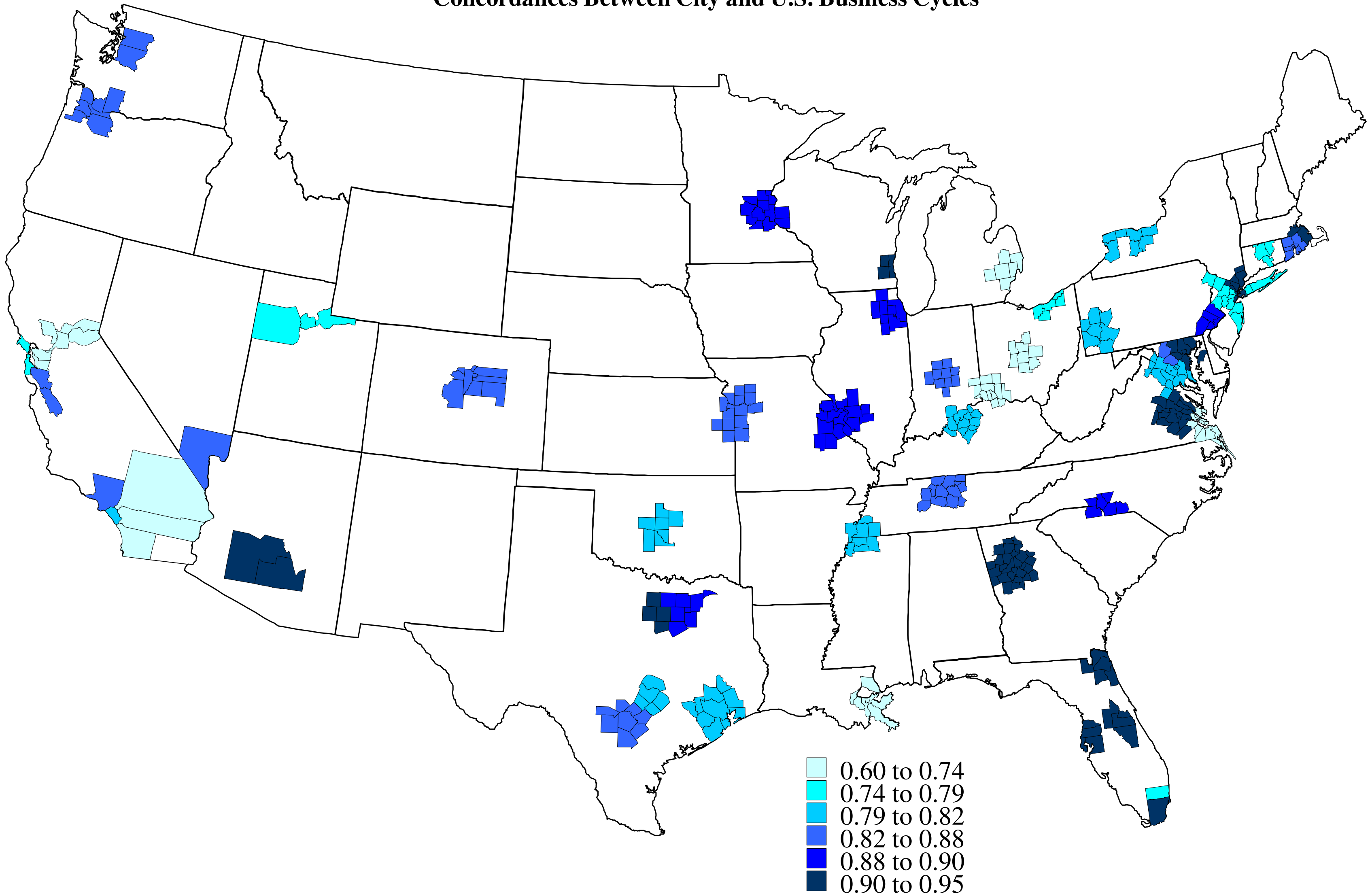


Figure 10.

City Effects in Percentage Points

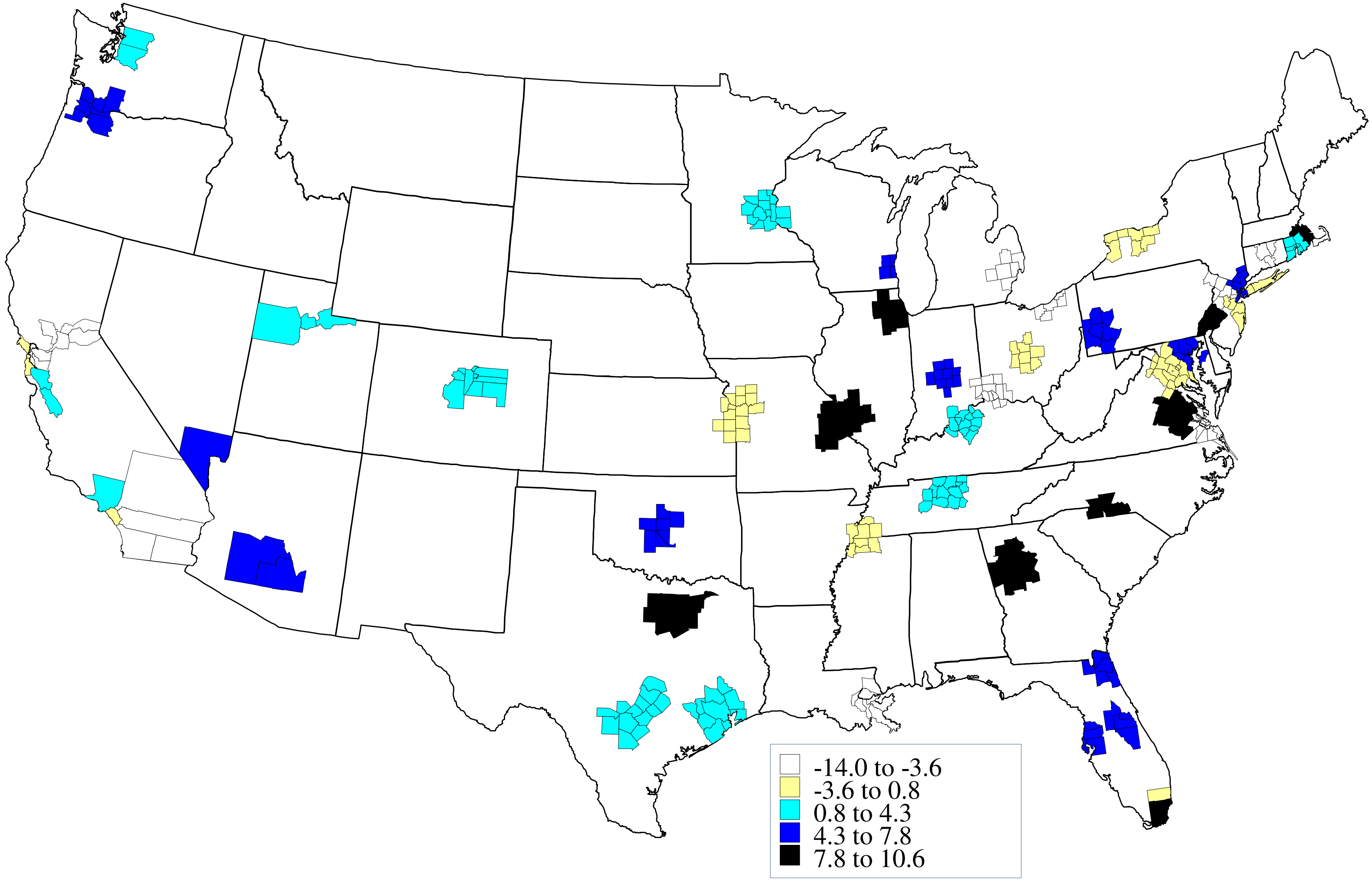


Figure 11. Employment by Race

Shaded areas are U.S. Employment Contractions

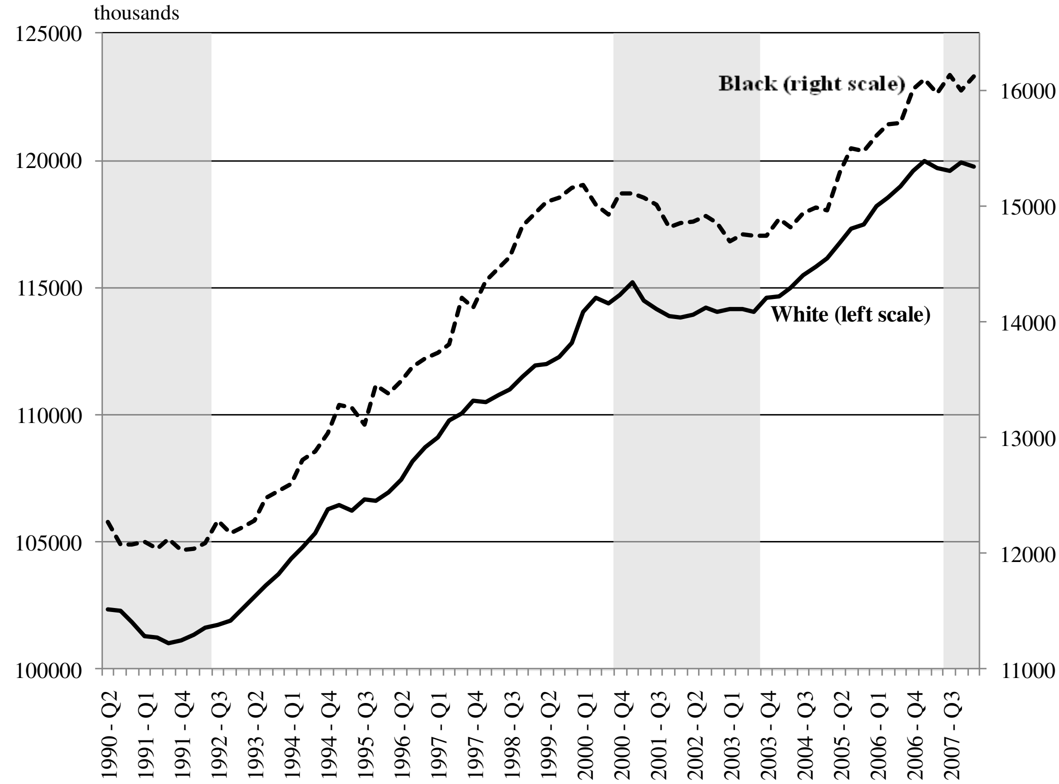


Figure 12. Employment by Educational Attainment

Shaded areas are U.S. Employment Contractions

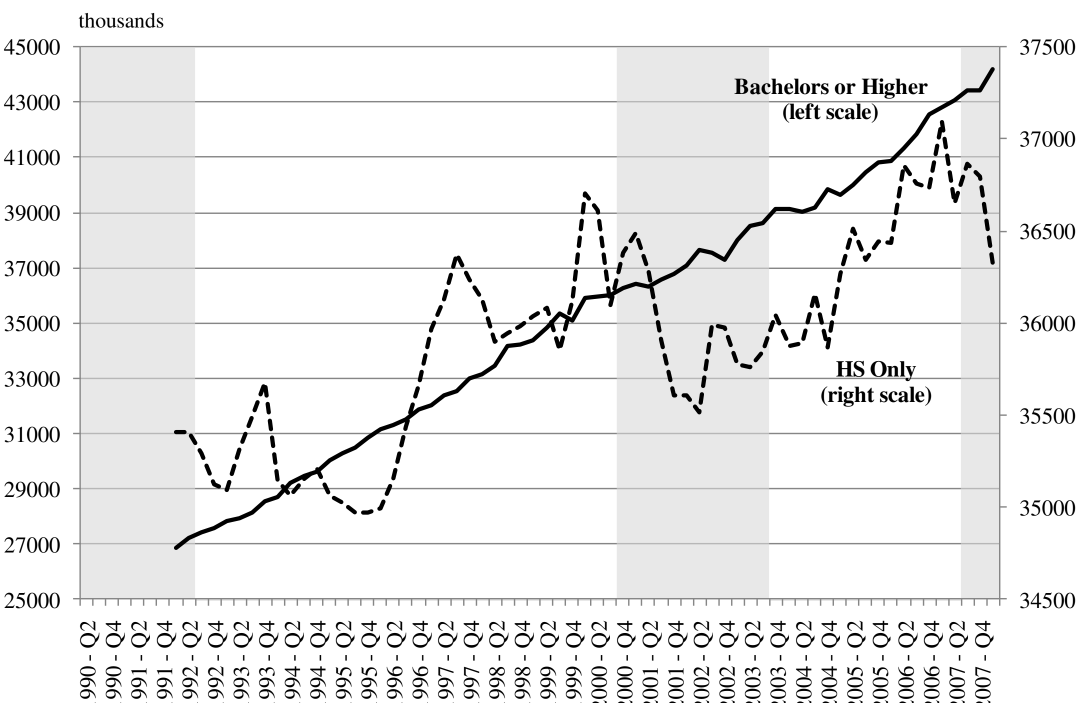


Table 1. The Occurrence of City-Level Contractions

(A █ indicates a contractionary quarter and shaded areas are US contractions)

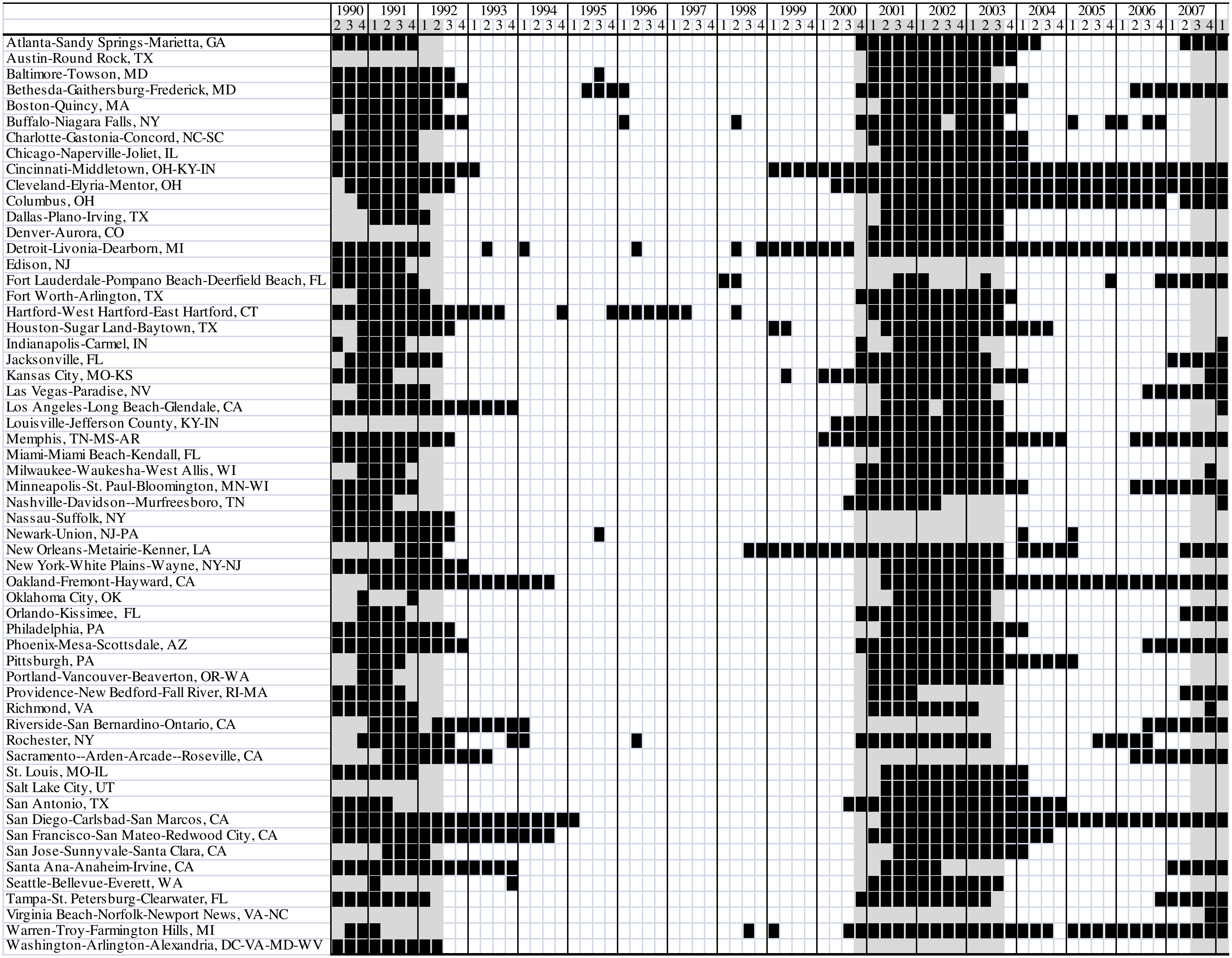


Table 2. Industrial vs. Geographic Similarity

	I	II	III	IV
Industrial Similarity Index	0.8135 (0.5393)		-0.0349 (0.5214)	-0.2570 (0.5130)
Same Principal State		0.1076* (0.0237)	0.1076* (0.0236)	0.1100* (0.0227)
Same Secondary State		-0.0343 (0.0317)	-0.0342 (0.0316)	-0.0468 (0.0331)
Same Region		0.0222* (0.0075)	0.0223* (0.0074)	
Both in Northeast				0.0550* (0.0191)
Both in South				-0.0106 (0.0110)
Both in Midwest				0.0953* (0.0269)
Both in West				0.0103 (0.0176)
Contiguous		0.0413 (0.0313)	0.0414 (0.0314)	0.0432 (0.0310)
Constant	4.3092* (0.0149)	4.2769* (0.0032)	4.2760* (0.0145)	4.2724* (0.0143)
Log Likelihood	1257.73	1306.45	1306.45	1318.65

The dependent variable is the log of the concordance between the two cities, all five models include city dummies, and all independent variables except for dummies are in logs. Statistical significance at the 5 percent level is indicated by "*". Standard errors are White-corrected.

Table 3. Robustness Across Measures of Industrial Similarity

	IVa	IVb	IVc	IVd
Industrial Similarity	-0.1908			
	(0.5609)			
Industrial Similarity (durables and nondurables)		-0.1915		
		(0.5791)		
Mining, Logging, and Construction Similarity			-0.0130	-0.0151
			(0.0921)	(0.0906)
Government Similarity			0.2401	0.2268
			(0.2059)	(0.2072)
Manufacturing Similarity			-0.1110	
			(0.0950)	
Durables Similarity				-0.0757
				(0.1362)
Same Principal State	0.1156*	0.1155*	0.1138*	0.1134*
	(0.0261)	(0.0261)	(0.0255)	(0.0255)
Same Secondary State	-0.0446	-0.0446	-0.0450	-0.0451
	(0.0340)	(0.0340)	(0.0339)	(0.0340)
Both in Northeast	0.0488*	0.0489*	0.0469*	0.0471*
	(0.0197)	(0.0197)	(0.0195)	(0.0196)
Both in South	-0.0021	-0.0021	-0.0011	-0.0011
	(0.0114)	(0.0114)	(0.0114)	(0.0115)
Both in Midwest	0.0960*	0.0960*	0.0964*	0.0956*
	(0.0271)	(0.0272)	(0.0271)	(0.0271)
Both in West	0.0064	0.0065	0.0065	0.0068
	(0.0177)	(0.0178)	(0.0178)	(0.0178)
Contiguous	0.0614	0.0615	0.0605	0.0613
	(0.0340)	(0.0340)	(0.0342)	(0.0343)
Constant	4.2732*	4.2729*	4.2811*	4.2827*
	(0.0156)	(0.0168)	(0.0107)	(0.0112)
Log Likelihood	1175.26	1175.26	1176.76	1176.42

The dependent variable is the log of the concordance between the two cities, all five models include city dummies, and all independent variables except for dummies are in logs. Statistical significance at the 5 percent level is indicated by “*”. Standard errors are White-corrected. Because of data availability, Austin, TX; Bethesda, MD; and Fort Lauderdale, FL are not included in this data set.

Table 4. Expected Concordances from Model IV

Two cities in:	Expected Concordance
1) different regions and states	71.7
2) the same state in the South or West	80.0
3) different Northeastern states	75.7
4) different Midwestern states	78.9
5) the same Northeastern state	84.6
6) the same Midwestern state	88.0

Table 5. Estimated City Effects from Model IV

City	City Effect (est. coeff.)	Standard Error	City Effect (% points)
Charlotte-Gastonia-Concord, NC-SC	0.1114	(0.0112)*	9.6
Miami-Miami Beach-Kendall, FL	0.1091	(0.0103)*	9.4
Boston-Quincy, MA	0.1002	(0.0088)*	8.5
Fort Worth-Arlington, TX	0.0993	(0.0089)*	8.4
Richmond, VA	0.0980	(0.0094)*	8.3
Dallas-Plano-Irving, TX	0.0942	(0.0102)*	7.9
Philadelphia, PA	0.0933	(0.0086)*	7.9
Chicago-Naperville-Joliet, IL	0.0928	(0.0111)*	7.9
St. Louis, MO-IL [5]	0.0916	(0.0117)*	7.8
Atlanta-Sandy Springs-Marietta, GA	0.0934	(0.0092)*	7.8
Baltimore-Towson, MD	0.0903	(0.0098)*	7.5
Portland-Vancouver-Beaverton, OR-WA	0.0885	(0.0127)*	7.4
New York-White Plains-Wayne, NY-NJ	0.0830	(0.0095)*	7.0
Jacksonville, FL	0.0840	(0.0077)*	7.0
Tampa-St. Petersburg-Clearwater, FL	0.0813	(0.0089)*	6.7
Milwaukee-Waukesha-West Allis, WI	0.0786	(0.0112)*	6.6
Orlando-Kissimmee, FL	0.0765	(0.0092)*	6.2
Phoenix-Mesa-Scottsdale, AZ	0.0632	(0.0126)*	5.0
Las Vegas-Paradise, NV	0.0604	(0.0230)*	4.8
Pittsburgh, PA	0.0590	(0.0115)*	4.7
Oklahoma City, OK	0.0563	(0.0141)*	4.5
Indianapolis-Carmel, IN	0.0533	(0.0133)*	4.3
Seattle-Bellevue-Everett, WA	0.0502	(0.0136)*	4.0
Minneapolis-St. Paul-Bloomington, MN-WI	0.0496	(0.0121)*	3.9
Houston-Sugar Land-Baytown, TX	0.0475	(0.0098)*	3.8
Denver-Aurora, CO [4]	0.0483	(0.0146)*	3.8
San Jose-Sunnyvale-Santa Clara, CA	0.0482	(0.0133)*	3.7
Austin-Round Rock, TX	0.0448	(0.0140)*	3.5
Salt Lake City, UT	0.0422	(0.0135)*	3.3
San Antonio, TX	0.0387	(0.0129)*	3.0
Nashville-Davidson--Murfreesboro, TN	0.0300	(0.0144)*	2.2
Louisville-Jefferson County, KY-IN	0.0262	(0.0151)	2.0
Los Angeles-Long Beach-Glendale, CA	0.0163	(0.0108)	1.2
Providence-New Bedford-Fall River, RI-MA	0.0106	(0.0134)	0.8
Kansas City, MO-KS	0.0093	(0.0123)	0.7
Buffalo-Niagara Falls, NY	-0.0155	(0.0089)	-1.1
Washington-Arlington-Alexandria, DC-VA-MD-WV	-0.0169	(0.0214)	-1.2
Memphis, TN-MS-AR	-0.0185	(0.0200)	-1.3
Rochester, NY	-0.0242	(0.0101)*	-1.7
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	-0.0259	(0.0131)*	-1.8
Bethesda-Gaithersburg-Frederick, MD	-0.0274	(0.0155)	-1.9
Edison, NJ	-0.0322	(0.0204)	-2.3
Nassau-Suffolk, NY	-0.0325	(0.0190)	-2.3
Santa Ana-Anaheim-Irvine, CA	-0.0451	(0.0140)*	-3.1
San Francisco-San Mateo-Redwood City, CA	-0.0465	(0.0127)*	-3.2
Columbus, OH	-0.0522	(0.0176)*	-3.6
Newark-Union, NJ-PA	-0.0576	(0.0164)*	-3.9
Virginia Beach-Norfolk-Newport News, VA-NC	-0.0859	(0.0230)*	-5.6
Cleveland-Elyria-Mentor, OH	-0.1023	(0.0229)*	-6.5
Hartford-West Hartford-East Hartford, CT	-0.1291	(0.0232)*	-7.9
Warren-Troy-Farmington Hills, MI	-0.1394	(0.0201)*	-8.4
New Orleans-Metairie-Kenner, LA	-0.1452	(0.0177)*	-8.5
Sacramento--Arden-Arcade--Roseville, CA	-0.1562	(0.0205)*	-9.2
Riverside-San Bernardino-Ontario, CA	-0.1828	(0.0196)*	-10.4
Oakland-Fremont-Hayward, CA	-0.2202	(0.0274)*	-11.9
Cincinnati-Middletown, OH-KY-IN	-0.2315	(0.0290)*	-12.3
San Diego-Carlsbad-San Marcos, CA	-0.2474	(0.0288)*	-12.8
Detroit-Livonia-Dearborn, MI	-0.2852	(0.0268)*	-14.0

Statistical significance at the 5 percent level is indicated by "*".

Table 6. More Covariates of Concordance

	V	VI	VII	VIII
Industrial Similarity	-0.3966	-0.4656	-0.5649	-0.4598
	(0.5179)	(0.5186)	(0.5275)	(0.5215)
Industrial Diversity			1.2155	
			(0.9447)	
Same Principal State	0.1072*	0.1071*	0.1075*	0.1070*
	(0.0227)	(0.0227)	(0.0227)	(0.0228)
Same Secondary State	-0.0485	-0.0462	-0.0457	-0.0462
	(0.0339)	(0.0339)	(0.0340)	(0.0339)
Both in Northeast	0.0561*	0.0571*	0.0580*	0.0573*
	(0.0192)	(0.0183)	(0.0183)	(0.0185)
Both in South	-0.0078	-0.0064	-0.0060	-0.0064
	(0.0112)	(0.0111)	(0.0111)	(0.0111)
Both in Midwest	0.0909*	0.0858*	0.0864*	0.0857*
	(0.0266)	(0.0265)	(0.0265)	(0.0265)
Both in West	0.0107	0.0131	0.0134	0.0131
	(0.0182)	(0.0190)	(0.0190)	(0.0190)
Contiguous	0.0420	0.0404	0.0403	0.0405
	(0.0315)	(0.0316)	(0.0316)	(0.0317)
Racial Similarity	-0.0108	-0.0209	-0.0296	-0.0208
	(0.1259)	(0.1233)	(0.1231)	(0.1236)
High School Attainment	0.2300*	0.2160*	0.2156*	0.2174*
	(0.0756)	(0.0755)	(0.0756)	(0.0778)
Bachelor's Attainment	-0.0732	-0.0631	-0.0596	-0.0612
	(0.0804)	(0.0802)	(0.0806)	(0.0820)
Average Bank Size		1.1743	1.1706	1.1832
		(0.7853)	(0.7854)	(0.7835)
Banks per Establishments		-2.2632	-2.1760	-2.2694
		(2.0817)	(2.0833)	(2.0853)
Mean Establishment Size		1.5899*	1.5615*	1.5921*
		(0.6339)	(0.6346)	(0.6372)
City-Density				-0.0067
				(0.0621)
City-Size				-1.6489
				(15.3058)
Constant	4.2776*	4.2919*	4.2954*	4.2913*
	(0.0170)	(0.0185)	(0.0186)	(0.0190)
Log Likelihood	1322.50	1327.15	1327.72	1327.16

The dependent variable is the log of the concordance between the two cities, all five models include city dummies, and all independent variables except for dummies are in logs. Statistical significance at the 5 percent level is indicated by "*". Standard errors are White-corrected.

Table 7. Expected Concordances From Model VI

Two cities in:	Different HS Attainment and Establishment Size[a]	Same HS Attainment	Same Establishment Size	Same HS Attainment and Establishment Size
1) different regions and states	73.1	74.5	74.7	76.2
2) the same state in the South or West	81.2	82.6	82.8	84.3
3) different Northeastern states	77.3	78.7	79.0	80.4
4) different Midwestern states	79.5	80.9	81.2	82.6
5) the same Northeastern state	85.9	87.3	87.5	89.0
6) the same Midwestern state	88.4	89.8	90.0	91.4

[a] The difference in high school attainment and average establishment size is the average across the city pairs.